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ABSTRACT

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This paper evaluates the sources of transitory market power in the market for personal computers (PCs) during the late 1980s. Our analysis is motivated by the coexistence of low barriers to entry into the PC industry and high rates of innovative investment by a small number of PC manufacturers. We attempt to understand these competing phenomena by measuring the role that different *principles of product differentiation* (PDs) may have played in segmenting this dynamic market. Each PD reflects some notion of product similarity and offers a potential source of market segmentation, in that products which share similar characteristics may be closer substitutes than products which belong to separate groups. Our first PD measures the substitutability between Frontier and Non-Frontier products, where the technological frontier is defined to include those computers which incorporate the Intel 80386 chip. The second PD measures the differentiation between those products sold by brand-name firms (IBM, Compaq, etc...) and those products sold by the non-branded fringe. Our modeling strategy is flexible enough so that neither PD is assumed, *a priori*, to be more important than the other. Expanding upon recent advances in the measurement of product differentiation, we measure the separate roles that technical advance (incorporating the 80386) and branding (e.g., by IBM) played in contributing to transitory market power. In so doing, this paper attempts to account precisely for the market origins of innovative rents in the PC industry.

Our principal finding is that, during the late 1980s, the PC market was indeed highly segmented along both the Branded (B versus NB) and Frontier (F versus NF) dimensions. The effects of competitive events (e.g., entry, imitation, price cuts) in any one cluster were confined mostly to that particular cluster, with little repercussion on other clusters. For example, less than 5% of the market share achieved by a hypothetical clone entrant would be market-stealing from other clusters. In addition, the product differentiation advantages of B and F were qualitatively different. The principal benefit associated with F was limited to the isolation it provided from the large number of NF competitors. In contrast, brand names shifted out the product demand curve as well as segmenting B products from NB competition. These results help explain, in a precise way, how transitory market power (arising from market segmentation) shaped the underlying incentives for innovation in the PC industry during the mid to late 1980s.

I. INTRODUCTION

Product innovations contribute to economic progress by expanding the range of choices available to consumers and by improving the performance dimensions of existing products. However, the incentives to innovate do not stem directly from the *social* value of new or improved products but from the *private* returns that innovators manage to capture in the marketplace. In order to be an effective inducement, these potential rents must be secured from the competitive threats posed by pre-existing products, from imitators, and, at least for some time, from products extending the technological frontier even further. As Arrow (1962) pointed out, innovators have to enjoy some degree of transitory market power in order to pay for their innovations. In this paper, we examine some of the critical measurement issues that arise in this context, by evaluating the sources of transitory market power in the market for microcomputers (commonly referred to as personal computers, or just PCS) in the late 1980s.

In differentiated, fast changing product markets, innovative firms might be able to take advantage of several different sources of transitory market power. First, new products might incorporate novel features, making existing products only an imperfect substitute for the new good. Second, firms may try to slow down the pace of rent-dissipation in the marketplace by extending the protective umbrella of a pre-existing brand-name reputation over new product introductions. To take advantage of this branding, innovators might exploit a widespread willingness to pay a brand premium; alternatively, the innovator might concentrate on serving high-margin niche markets for the latest offerings from "high-quality" branded producers (Teece, 1988).

Of course, the classical justification for patents, trademarks, and other forms of formal intellectual property protection is precisely their ability to provide temporary monopoly power in order to prompt innovation and creativity; yet, these forms of protection seem to have played only a minor role in ensuring innovative rents in the PC industry during the late 1980s.[1] Consequently, we focus here on the role that pushing the technological frontier (in this case meaning the incorporation of the 80386 microprocessor) and relying on a brand name reputation (such as that of IBM) played

[1] Patents did not substantially delay the entry of imitators as the industry is organized around an open technical standard. Thus, our industry is like the majority of those studied by Levin et al. (1987) in the modest role played by patents in ensuring appropriability.

in ensuring transitory market power to innovative PC firms.

Our starting point is the fact that markets for differentiated products often exhibit some form of segmentation or clustering according to a small number of "principles of differentiation" (PDs). Each PD defines a distinct notion of product similarity according to the presence or absence of some key product characteristic and offers a potential source of market segmentation. Thus, products that belong to the same cluster (defined by these PDs) would be closer substitutes to each other than to products belonging to other clusters. We consider here two such principles: whether or not the product is associated with a strong brand name (Branded, B, versus Non-Branded, NB) and whether or not the product is at the cutting edge of the technological frontier (Frontier, F, versus Non-Frontier, NF). Both contemporary industry sources as well as retrospective analysis support the view that the late 1980s market for personal computers indeed exhibited the 4-way clustering implied by these two PDs: {B, F}, {B, NF}, {NB, F}, and {NB, NF}.[2] The model of demand that we estimate, the instruments that we use for that purpose, and the issues that we address with the estimates all stem from and build upon these two principles of differentiation.

We devote the bulk of the paper to the estimation of a discrete choice model of demand for PCS that allows us to evaluate the substitution patterns within and across these PDs. To do so, we draw from and extend recent methodological advances in the empirical study of product differentiated markets (Bresnahan 1981, 1987; Trajtenberg, 1990; Berry, 1994; Berry, Levinsohn, and Pakes, 1995). Following Berry (1994), we motivate the functional form for the demand system by modeling a discrete choice maximization problem faced by a set of heterogeneous consumers. We then account for the potential correlation between price and unobserved quality by utilizing a set of instruments based on the attributes of competing products using a model of competition. The specific model that we put forward, the "Principles of Differentiation (PD) Generalized Extreme Value (GEV)," is a particular application of the GEV class of models suggested by McFadden (1978). The PD GEV allows us to treat different potential sources of segmentation symmetrically, thus overcoming the hierarchical structure (and concomitant limitations) of the familiar Multi-Level Nested Logit model. Finally, we take advantage of our priors about the prevailing principles of differentiation and use

[2] As a matter of semantics, we shall refer to each of these groupings as *clusters* (notice that PCS belonging to the {NB, NF} cluster are commonly referred to as "clones").

instrumental variables that reflect "local" (i.e., within-PD) competitive conditions, thus exploiting an additional source of variation in the context of our short panel dataset.

Our main findings are, first, that the PC market was indeed highly segmented during the late 1980s, along both the F and the B dimensions. Consequently, the effects of competitive events (such as entry, imitation, or price cuts) in any one cluster were confined mostly to that particular cluster, with little repercussion on the others. For example, our simulations imply that less than 5% of the market share achieved by a hypothetical clone entrant would be market-stealing from other clusters. The second finding is that the product differentiation advantages of B and F were qualitatively quite different. The advantage associated with positioning a product at the technological frontier was limited to the relative isolation that it provided from the large number of NF competitors. By contrast, bestowing a brand name reputation on a new product not only provided some protection from competition from non-branded PCS, but also shifted out the product demand curve a great deal.

The paper is organized as follows. In Section II we discuss some key features of the PC market in the late 1980s, including sources of buyer heterogeneity and the appropriateness of the clustering scheme proposed. We then describe the data, consisting of market shares, prices and attributes for each PC product sold in 1987 and 1988. In Sections IV and V, we develop the Principle of Differentiation GEV model, review its implementation, and present and discuss the set of instruments used in the estimation. We present the main results in Section VI, assess their robustness, and perform some simulations that highlight the extent of segmentation. Section VII concludes.

II. THE PC MARKET IN THE LATE 1980s[3]

Technical change in personal computing has been extremely fast and sustained; moreover, the nature of competition among PC firms has changed over time as well. Our snapshot of the market in 1987-88 catches the technology in swift transition with the introduction of a new microprocessor, the

[3] We limit our analysis IBM PCS and IBM-compatible PCS. Following industry convention at the time, we exclude both older, 8-bit computers (Apple II, CP/M, etc.) and incompatible architectures such as Apple Macintosh. While Macintosh and IBM-compatible machines would converge in capabilities over time (particularly during the early 1990s), there was little important overlap among commercial customers during the period under study.

80386, which we associate here with the Frontier. The role played by brand-name reputation is also highlighted, a role that would evolve and mutate later on, as the identities and types of firms with substantial brand capital changed. At the time when the 80386 was introduced (in late 1986), the design and production of microcomputers making effective use of the new chip posed considerable technical difficulties, and required substantial R&D efforts from PC makers.[4] By the end of 1986, only the most technically capable PC firms had succeeded in introducing an 80386-based system. A handful of other PC makers would see their development efforts succeed during our sample period, whereas most other firms took even longer to come out with marketable 386 designs.

A key question posed in this paper is the extent to which PCS that belonged to the Frontier (or were marketed by a Brand) were insulated from competition by Non-Frontier (Non-Branded) products. The answer to this question crucially depends on the degree of *heterogeneity* among buyers in their valuation of Frontier and/or Branded status. In the presence of substantial heterogeneity, Frontier (and Brand) can be protected from the competition of Non-Frontier (and Non-Brand), while at the same time coexisting with these products, neither group eliminating the other.

A close-up look at the transition from 286- to 386-based PCS suggests that there were indeed pronounced differences across buyers in their assessment of the prospective benefits of 386-based PCS. From an engineering perspective, the new systems yielded substantial improvements in the ability to run software due to the increased speed of the microprocessor and an improved address model for the main memory. However, some users (and analysts) saw 386-based systems just as faster versions of older PCS. Others, already running or planning to run more advanced and demanding software (such as the new Microsoft/IBM operating environment, Windows), saw them as the only sufficient platform that would satisfy their computing needs within the useful life of the

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[4] By the mid-1990s, it has become much easier to incorporate frontier technology into PC design. This is because a much higher share of PC innovation has become embedded in the components themselves (such as an Intel microprocessor) rather than in the integration among components (see Henderson and Clark (1990) for a discussion between component-based versus integration-based innovation). In the era under study in this paper, the opposite was true. PC equipment manufacturers had to develop specialized skills and make substantial expenditures in order to market a product on the technological frontier (Steffens, 1994).

current purchase. These conflicting opinions, echoed in lively debates in the trade press, presumably led to significant differences among buyers in their willingness to pay for the much more capable but also much more expensive 386-based PCS.[5] We would expect such heterogeneity to result in a steeply sloped demand curve for the Frontier PCS, as well as in poor substitutability between Frontier and Non-Frontier systems. Our model will measure these features of demand, and hence the extent to which Frontier PCS were insulated from Non-Frontier competition at that time.

PCS differed not only in terms of their technical features, but also in terms of the brand-name reputation that the manufacturers bestowed on them. During our sample period, PC buyers valued Brandedness as an indicator of high quality service and support from selling firms, as well as an indication that the product was reliable and practical for business applications. IBM, the leading brand name in the PC market for many years, was not just the inventor of the dominant design in PCS but also enjoyed a reputation for service, support, and technical excellence from making and marketing larger computers to business customers. Other large electronics firms also had preexisting reputations; of these, we treat AT&T and Hewlett Packard as branded based on, (*I*) their market and technological leadership in industry segments close to PCS; and (*ii*) their stated commitment to the business-oriented PC market segment, backed up by substantial advertising and marketing expenditures.[6] The fourth firm we treat as branded, and the only specialized PC firm so treated, is Compaq. The largest advertiser in the PC market at the time, Compaq built its brand name by establishing a reputation for innovation in PCS (such as its introduction of the first 386-based PC prior to IBM) and by providing reliable service and support for these frontier products (Steffen, 1994). Within a few years after our sample, several other firms built substantial brand reputations by imitating Compaq's strategy; however, except for Compaq, none had been successful prior to

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[5] O'Malley (1989) summarized both sides of the debate: "While a 386 or 386SX system often is a wiser purchase than a 286, those suggesting the demise of the 286 misunderstand the scope and diversity of PC applications."

[6] Other large computer companies sold PCS, but primarily to their existing customers rather than in a mass market. We treat these, including Burroughs, Honeywell and Wang, as Non-Branded.

1988.[7]

As with Frontier status, the issue of the degree of insulation from competition that branded firms enjoyed vis a vis non-branded ones, hinges largely on the extent to which buyers heterogeneously value the attributes signaled by brandedness. A branded company's reputation for service, support, and product reliability presumably is valued by *all* buyers (and we will measure that). Some buyers, however, may have particularly high valuations for these firm-related attributes, and presumably will be willing to pay an even higher premium for Branded products. In fact, this sort of heterogeneity was widely reported for PC purchases in our sample period.[8] Buyers in large organizations (e.g. those in the Fortune 500) tended to favor branded PCS over those offered by clone makers. Other, usually smaller, organizations valued brandedness significantly less tending to buy the cheaper clone computers. In our primary specification, we treat IBM, AT&T, HP and Compaq as a separate branded group, and seek to measure how insulated their PCS were from competition from clones.[9]

In principle, not just Frontier and Brand but other aspects of PCS, technical and otherwise, could have been the source of market segmentation and hence of temporary monopoly power. However, IBM's historic decision to have an open architecture for PCS (and the decision of the other PC firms at the time of our sample to be strictly compatible), allows us to eliminate outright a whole class of potential sources of market segmentation. IBM's open architecture meant that buyers could "mix and match" a wide range of peripherals and add-in cards; therefore, price differentials between PCS due to such components could be arbitraged away.[10] Given the existence of a competitive retail

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[7] Dell Computer would be the next entrant into the Branded segment through the development of a reputation for excellent service and support in conjunction with substantial advertising.

[8] See Ryan (1987), Jenkins (1987), and Kolodziej (1988).

[9] In related specifications, we also examine whether IBM was further separated from other branded firms. We also experiment with the boundary of the branded segment. Other marketing variables, such as distribution channels (store/mail order) may have been important but do not receive special treatment in our models.

[10] Some PCS are limited in the amount of RAM they can maximally hold. Up to this limit, however, buyers can typically populate the computer with more of less RAM according to their

market for unbundled components, variations in attributes such as the amount of RAM, or the size of the hard disk, could not make one PC a poor substitute for another. We therefore treat these characteristics as hedonic attributes, in the sense that we allow them to shift the relative level of demand for each PC but not to affect the substitution patterns between products.[11]

Having focused here on the sources of *transitory* market power, it is important to put our sample period in perspective, sketch the forces that brought rapid change to the PC industry, and transformed time and again the patterns of competition in it. Both the supply of technically advanced PCS and the demand for desktop computing are being shifted continuously by powerful dynamic processes. The PC sector itself is technically progressive. Immediately upstream lie other fast-paced, innovative industries such as integrated circuits, mass storage devices, and so on. The introduction of ever faster microprocessors, memory chips, and disk drives frequently shifts out the invention-possibilities curve in PCS themselves. There are also a variety of technically progressive industries downstream. Software products like operating systems, word processors, and spreadsheets advance rapidly, pushing out the demand for more technically advanced PCS.

These relentless changes mean that both sources of segmentation that we seek to measure, Frontier and Brand, were shifting rapidly. Shortly after our period, a much larger number of companies sold 386-based PCS. Later still, newer and faster microprocessors heralded a new frontier. In the same era, a number of firms improved marketing operations, especially delivery and customer support, thereby approaching Branded status. In the early 1990s, the principal suppliers of microprocessors and operating systems, Intel and Microsoft respectively, came to hold much of the control of PC standards that IBM was losing in our sample period.[12] The current PC industry

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budget and the software they seek to run. Sellers typically picked these limits so that they did not bind on customers early in the life of the machine.

[11] An intermediate case is microprocessor speed, expressed in MHZ. Buyers could not arbitrage it, since speed is "designed into" the microprocessor and controller card. The availability of several different processor speeds with most models somewhat mitigated this effect since, in most cases, buyers could find their ideal point nearly met by an offered variation. We examine this issue in a variant of our base specification.

[12] During and after our sample period, IBM attempted to regain control of PC market standard setting via the OS/2 operating system and the introduction of a novel (and proprietary)

structure, with multiple technically capable branded firms competing, emerged from these events. There is little doubt that these changes destroyed much of the transitory market power that we seek to measure in a moment of transition. However, the private incentives to innovate arise from the discounted (expected) value of the rents which accrue in each period; in this sense, the period-specific measurement of transitory market power is a key step towards understanding innovative investment in dynamic technology-intensive markets.

III. THE DATA

Estimating a product-level differentiated demand system requires data on quantities sold, prices, and characteristics of each make/model in each year. Estimates of total market size are also needed. The dataset that we gathered for the present study consists of all PC make/ models (boxes) for which accurate data on price and attributes could be obtained for 1987 and 1988. Identifying a comprehensive, well-defined set of distinct make/models constituted a major stumbling block. Because of the difficulties encountered in gathering accurate data for each and every box, we restricted the scope of the dataset to those vendors with a relevant market presence (see Table 1). The resulting sample consists of 121 make/models (observations) for 1987, and 137 for 1988.[13]

Quantities were obtained from a database provided by COMTEC Market Analysis Services, covering the years 1987 and 1988. COMTEC reports in great detail purchases of information technology (IT) equipment (including PCS) by a large, weighted sample of business establishments in the U.S.[14] Using COMTEC's weighting scheme, one can extrapolate from the sample data to calculate the total number of PCS sold for each make/model. Since COMTEC samples business establishments in the U.S. whether or not they purchased PCS, one can use the same weighting

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PC design (Micro-Channel Architecture). Ultimately, IBM's strategy to regain standard setting leadership failed.

[13] See Appendix A for a detailed description of the data gathering methodology. Appendix B provides precise definitions of all variables used in the analysis.

[14] The COMTEC "Wave 6" dataset that we use here is based on a sample of over 6,000 establishments. Note that the sample excludes households.

scheme to estimate the total *potential* market size for desktop business PCS. For our purposes we take the potential market to be the total number of office-based employees (39 million.) The model that we estimate includes an "outside good" (that is, the option of not buying), and therefore market shares are computed as unit sales of each make/model divided by 39 million.

Our price and characteristics data come from the GML MicroComputer Guide, as well as from a wide variety of additional sources. We focused on a small number of critical technical characteristics including the microprocessor, the standard RAM provided (expressed in KB), the speed (MHZ), and the standard hard disk provided (DISK, in MB).[15]

As mentioned above, our analysis relies heavily on the possible existence of two principles of differentiation in the PC market at the time: whether or not the PC was at the technological frontier and whether or not it was produced by a branded firm. We capture the former with a dummy variable (FRONTIER) that assigns the value of 1 to PCS incorporating the 80386 microprocessor, and 0 to those with all other microprocessors (the 286, 8088, and older). As mentioned in Section II, we identified four vendors for which a brand name was a potentially important determinant of demand and substitution patterns: IBM, AT&T, Hewlett-Packard and Compaq.[16] The variable BRANDED assigns 1 to products produced by these four firms and 0 to products produced by other vendors.

Tables 2-4 provide a useful portrait of the PC industry in each of the years under study. Though the two samples are only a year apart, there are substantial differences in the average price/performance of PCS sold. Whereas the average price changed only slightly between the two years ($3,225 to $3,205), the average hard disk size (DISK), speed (MHZ), and memory (RAM) all increased substantially. For example, the average standard RAM increased from 611 KB to 688 KB. Indeed, the average level of each of these characteristics rose over 10% between the two years. The rate of technical advance is accentuated if the observations are weighted by the

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[15] These are the characteristics actually used in the estimation. We also collected information on the monitor type (B&W or Color), whether the machine was portable, model vintage, etc.

[16] Other configurations were attempted; the qualitative results are not affected by the inclusion or exclusion of branded firms at the margin.

quantities sold. For example, the weighted average standard RAM rises from 584 KB to 716 KB. The rate of advance shows also in the share of 386-based PCS (i.e., the average for FRONTIER), which grew from 10% of the sample in 1987 to 15% in 1988. By contrast, the number of BRANDED products stayed nearly constant, averaging 30% of the number of make/models marketed in both years. The advance in the price/performance ratio is highlighted in a regression of price on the observed product characteristics (Table 3). The coefficients for each of the technical characteristics are estimated to be positive, while the 1988 coefficient is substantially lower than for 1987. While a substantial amount of price variation exists in each year, our sample reflects the rapidly falling real prices for computing power which has characterized this market segment since its inception (Berndt and Griliches, 1993).

Finally, we "slice" the data according to our PDs (Branded and Frontier) in Table 4. Perhaps the most striking statistic from this table is that while a relatively high share of all products are concentrated in the NB/NF cluster, at least 60% of the boxes sold in each year are drawn from the B/NF cluster. Moreover, the average price for boxes rises as one moves from the "clone" NB/NF cluster through NB/F (or B/NF), with the highest average prices in the B/F cluster. While this preliminary cut of the data suggests the presence of substantial returns to membership in either the F or B group, one cannot identify the precise way in which these returns manifested themselves (through the benefit of a large demand curve, or, alternatively, a steep one) from this simple table. Instead, our more systematic evaluation of the returns to membership in the B or F group will follow the estimation of the differentiated product demand system, the model to which we now turn.

IV. MODELING THE DEMAND FOR PCS

The rest of this paper is devoted to estimating a model of PC demand which allows us to evaluate precisely the origins of transitory market power and isolation from competition in the PC market during 1987-88. We measure the demand for PCS at the product level and explore the different competitive positions of PCS which incorporated different attributes. [17] Our model, based

[17] We exploit and extend recent methodological advances which have expanded the range of economic models which can be estimated with product-level data (Bresnahan, 1981, 1987; Trajtenberg, 1990; Berry, 1994; Berry, Levinsohn, and Pakes, 1995).

on the familiar random utility model, aggregates from individual buyer heterogeneity to product level demand. Besides corresponding to PC market reality, this permits straightforward treatment of new products and of products no longer being sold. Our model is novel in that it permits the existence of non-overlapping principles of differentiation (like brandedness and frontiers status) without calling for difficult numerical integration.

A. THE RANDOM UTILITY APPROACH TO DEMAND ESTIMATION

Our model of PC demand is motivated by the theory of random utility (Quando, 1956), as developed in the "Generalized Extreme Value" (GEV) class of models put forward by McFadden (1978) and following Berry's recent proposal for the estimation of such models (Berry, 1994). Our point of departure is a discrete choice random utility model. Each buyer is assumed to maximize by choosing among J_t+1 alternatives (J_t marketed products in year t and the option of no purchase (j=0)), as follows,

$$\underset{j \in \{0,\ldots,J_t\}}{\text{MAX}} \; V_{ij} = X_j'\beta + \alpha p_j + \xi_j + \eta_{ij} \tag{1}$$

where V_{ij} is the value of product j to buyer I. For product j, X_j is a vector of observed product characteristics, p_j is the price and ξ_j is the level of unobserved product quality.

Our treatment follows Berry (1994), decomposing V_{ij} into two parts. Let

$$\delta_j = X_j'\beta + \alpha p_j + \xi_j \tag{2}$$

be the <u>mean valuation</u> by buyers for product j. Thus, η_{ij} is the difference between buyer I's value for product j from the average valuation in the population (δ_j). Each buyer receives a draw of the J_t+1 vector, η_i, which is a realization of the random variable η. The draws are independent across buyers but a given buyers' draw of η_{ij} need not be independent of η_{ik} if products j and k share similar product characteristics. The distribution of η depends on parameters ρ and the product characteristics X. We write this (J+1 dimensional) CDF as $F(\eta; X, \rho)$. Thus, $\{\beta, \alpha, \rho\}$ is the vector of parameters to be estimated in this discrete choice demand system.

Since the work of Quandt (1956), we have known that the distribution of the random shocks to valuation, here η, is a key determinant of the shape of demand. In the context of our discrete choice model, there is in fact a precise relationship between the distribution of η at the individual buyer level and the pattern of cross-product elasticities at the aggregate market level. The modeler picks a family of distributions $F(\eta; X, \rho)$. Particular values of the parameter vector ρ correspond to patterns of dependence in η across products sharing common (or similar) product characteristics. Our model contains a parameter ρ_F, for example, which permits dependence across the idiosyncratic shocks to Frontier products. For certain values of ρ_F, a buyer strongly preferring any Frontier product ($\eta_{ij} >> 0$) is also likely to strongly prefer all Frontier products ($E[\eta_{ik} \mid \eta_{ij} >> 0] >> 0$] if k and j share Frontier status.)

Now consider the impact of an increase in the price of particular product j: the value of product j falls (at a rate α) and some portion of those consumers whom had initially chosen j are induced to switch to what had been previously their second-best alternatives. Because of the dependence in the distribution of η, a relatively high share of these second-best alternatives will be other Frontier products. More generally, positive dependence in the distribution of η among similar products makes those products closer substitutes.[18] The parameters ρ measure that dependence. As dependence in η across products with similar products characteristics becomes stronger, competition will become more "segmented," in the sense that the impact of competitive events (such as a price decrease or entry) will be confined mostly to those products with similar characteristics. In other words, in this framework a model of which classes of products are close substitutes <u>is</u> a model of dependence among the elements of η related to product characteristics.

B. A PRINCIPLES OF DIFFERENTIATION GEV MODEL OF PC DEMAND

Of course, a separate question exists as to how to identify those product characteristics which may be important for understanding differentiation and market segmentation. Fortunately, economic

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[18] This type of dependence across observations can be contrasted with the case where η is iid across choices (as in the multinomial logit). Under the assumption of independence, the introduction of a new product will have the same (proportional) effect on all products in the market, regardless of characteristics. This implication of the iid assumption is just a restatement of the "Red Bus/Blue Bus" problem emphasized by McFadden (1973).

theory, in conjunction with an understanding of the particular market under study, provides considerable guidance. Like many other consumer products, there exists several features of the PC (such as the amount of RAM or the size of the hard drive) for which there exists a separate market for that feature (or component). In the presence of competitive component markets, buyers will arbitrage away price premiums associated with the incorporation of these components into particular products. In other words, to the extent that consumers can "repackage" products along a specific dimension, each consumer will equate their marginal utility for this dimension to its price in the post-sales market. Accordingly, there will be no ex-post heterogeneity among consumers in their marginal valuations for this dimension. Thus, in choosing how to parameterize the distribution function $F(\eta; X, \rho)$, one should incorporate potential correlation among products which share characteristics which are not "repackageable."

Guided by this rule, we focus on two product characteristics which we argue are not repackageable -- Branded and Frontier. The existence of a Brand name reputation, by construction, cannot be marketed in the post-sales market. As well, during the period under study, considerable technical expertise was required to incorporate the 80386 microprocessor into a PC. In contrast, buyers could entertain several post-sales options to reconfigure their memory options (e.g., RAM and DISK) and, to a lesser extent, the speed of their microprocessor (MHZ).

To accommodate the presence of non-mutually exclusive product groupings (i.e., PDs) in a computationally straightforward specification, we need to parameterize $F(\eta; \rho)$ so that several PDs can be incorporated symmetrically into the distribution function. To do so, we rely upon Theorem 1 of McFadden (1978), which states a significant generalization of the nested multinomial logit (NML) model. McFadden introduces the Generalized Extreme Value (GEV) model through a constructive proof demonstrating that a wide variety of dependencies (and thus patterns of substitution) are consistent with random utility maximization:

Proposition 1 (Adapted from Theorem 1, McFadden (1978)): If $G: R^{J+1} \rightarrow R^1$ is a non-negative, homogeneous of degree one function satisfying certain restrictions,[19] then

$$F(\eta_{i0},\ldots,\eta_{iJ}) = \exp -G(e^{-\eta_{i0}},\ldots,e^{-\eta_{iJ}}) \tag{3}$$

is the cumulative distribution function of a multivariate extreme value distribution, and

$$s_j = \frac{e^{\delta_j}\, G_j(e^{\delta_0},\ldots,e^{\delta_J})}{G(e^{\delta_0},\ldots e^{\delta_J}).} \tag{4}$$

is the corresponding equation determining the market share of product j, where G_j is the partial derivative of j with respect to $e^{\delta j}$.

McFadden (1978) suggests that Proposition 1 can serve as a straightforward and general purpose specification tool: by specifying the function G(·), the modeler chooses the pattern of dependency of η_{ij}s across products. Thus, Proposition 1 provides a method for parameterizing the cross-product substitution matrix. Our model will utilize this theorem to parameterize a random utility model which incorporates *non-nested* cross-product correlations in η.[20]

In order to make the logic of the theorem more understandable, consider the G(.) function associated with a traditional specification, the one-level NML. To incorporate potential correlation among products according to whether or not the product is at the technological frontier (F versus NF), the function G(·) takes the form,

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[19] The limit of G (·) as any argument goes to ∞ must be equal to $+\infty$. Mixed partials of G(·) must alternate in sign and first partials must be non-negative (McFadden, 1978).

[20] Most previous research has implemented some version of the NML (a special case of the structure in Theorem 1). We are aware of only one other empirical study (Small, 1987) which utilizes McFadden (1978) to parameterize a non-nested structure.

$$G(e^{\delta}) = \left(\sum_{j \in F} e^{\delta_j / \rho_F}\right)^{\rho_F} + \left(\sum_{j \in NF} e^{\delta_j / \rho_F}\right)^{\rho_F} + e^{\delta_0} \tag{5}$$

where the parameter ρ_F parameterizes the degree of substitutability among products with the same Frontier status (F or NF) relative to the substitution among non-matching products.[21] To be consistent with (1), the distributional parameter ρ_F must lie in the unit interval. As ρ_F goes to 0, the dependence across products which share F or NF status becomes stronger. Conversely, as ρ_F goes to 1, (5) simplifies to the G function associated with a simple multinomial logit model (i.e., each element of η is independent).[22]

In our application, we are interested in parameterizing the potential correlation among products along (at least) two distinct dimensions (F/NF and B/NB). To accommodate this in the most straightforward way, we compose $G(\cdot)$ to be the weighted sum of two one-level NML $G(\cdot)$ functions, as follows:

$$G(e^{\delta}) = a_F\left[\left(\sum_{j \in F} e^{\frac{\delta_j}{\rho_F}}\right)^{\rho_F} + \left(\sum_{j \in NF} e^{\frac{\delta_j}{\rho_F}}\right)^{\rho_F}\right] + a_B\left[\left(\sum_{j \in B} e^{\frac{\delta_j}{\rho_B}}\right)^{\rho_B} + \left(\sum_{j \in NB} e^{\frac{\delta_j}{\rho_B}}\right)^{\rho_B}\right] + e^{\delta_0} \tag{6}$$

where $a_F + a_B = 1$, and ρ_F and ρ_B are between 0 and 1.[23] Because we introduce terms composed of products which share PDs, we denote this model the PD GEV. The only difference between (6) and more traditional nested logit models of product differentiation (e.g., (5)) is that each product

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[21] The other parameters to be estimated (β and α) are included in δ.

[22] The precise statistical interpretation of ρ, particularly in the case of a multi-level nested logit, is subtle. See Cardell (1992) for a fuller discussion of the distributional assumptions and the variance components structure of the NML model.

[23] The scaling parameters are defined as follows,

$$a_F = \frac{1-\rho_F}{2-\rho_F-\rho_B}, \quad a_B = \frac{1-\rho_B}{2-\rho_F-\rho_B}$$

Since the weights (a_F and a_B) are positive, all of the homogeneity, derivative, and limiting properties needed for Proposition 1 are true. As either ρ goes to 1, the associated weight goes to zero. This takes (6) smoothly to (5); At $\rho_{PD} = 1$, PD is not important for segmentation.

contributes to a term which measures its substitution with products which share technological status (F or NF) *and* in a term which measures its substitution with products which share marketing status (B or NB). Note that if $\rho_F = 1$ the model is a nested logit by Branded status only, and if $\rho_B = 1$ the model is nested by Frontier status only.

The implications of (6) for substitution in the market can be seen more clearly in terms of the market share equation for each product. Letting B(j) and F(j) denote the groups to which product j belongs,

$$s_j = \frac{a_F \dfrac{e^{\delta_j/\rho_F}}{\sum_{k \in F(j)} e^{\delta_k/\rho_F}} \left(\sum_{k \in F(j)} e^{\delta_k/\rho_F} \right)^{\rho_F} + a_B \dfrac{e^{\delta_j/\rho_B}}{\sum_{k \in B(j)} e^{\delta_k/\rho_B}} \left(\sum_{k \in B(j)} e^{\delta_k/\rho_B} \right)^{\rho_B}}{G(e^{\delta})} \tag{7}$$

Notice that this share equation is composed of two terms, one for F and one for B, the numerator of which is proportional to the one-level NML. Consider a product located in {B(j), F(j)}; then, changes in the prices or attributes of products located also in the same cluster {B(j), F(j)} will have a relatively strong impact on the market share of product j, whereas changes in products which are neither in B(j) nor in F(j) will have a lesser impact. Clearly, the impact of changes in products that share just one PD with product j will be somewhere in between. Each of these effects is stronger as the relevant ρ goes to zero.

While our proposed model, (6), is quite simple, Proposition 1 can accommodate a wide range of different clustering structures, including a larger number of "principles of differentiation," interactions between them, etc. Incorporating additional dimensions of potential product differentiation simply requires adding suitable terms to (6).[24] In this sense, the McFadden Theorem provides a useful and underutilized modeling tool with potentially wide applicability.

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[24] We have estimated several variant models (only a subset of which are presented in the Results Section). We have experimented with additional clustering by MHZ (as in Small ,1987), an "IBM" cluster, as well as others.

C. THE PD GEV VERSUS ALTERNATIVE MODELS OF SUBSTITUTION

Given our goal to measure the degree of segmentation afforded by (at least) two distinct PD's (B/NB and F/NF), several issues arise which make the most traditional (and computationally straightforward) parameterizations of the joint distribution of η inappropriate for our problem. First, because we want to distinguish between several different sources of product differentiation, we cannot employ a simple unidimensional *vertical* product differentiation (VPD) specification (Bresnahan, 1981, 1987; Berry, Carnall and Spiller, 1996; Stavins, 1996), in which a single distributional parameter measures variation among consumers in their preferences for overall product quality. As well, a nested multinomial logit (NML) model (Trajtenberg, 1990; Goldberg, 1995; Stern, 1996), in which several mutually exclusive dimensions of product differentiation can be incorporated, is also inappropriate. For example, if we were to specify (1) to be a two-level nested logit with the top level of the nesting determined by the B/NB distinction (Figure 1), we would be assuming away potential correlation in η (and the resulting implications for market-level substitution) among products which share Frontier status but *do not* match along the B/NB dimension. Thus, neither the VPD and NML models can parameterize our principal hypotheses directly -- the separate existence of segmentation along two overlapping dimensions (F/NF and B/NB).

In order to assess the relative merits of the PD GEV, it is worth comparing it in more detail to the two-level NML (see Figure 1). It is important to note that our proposed model (6) is no more richly parameterized than a two-level NML. Instead, the difference between the two models is that the PD GEV accommodates substitution in a way that we argue is more *appropriate* for our application. In particular, while in both models products sharing *both* B and F status are closer substitutes to each other than to other products, the models differ in their treatment of substitution among the *partially* matching products (note that the groups in the PD GEV are *not* mutually exclusive).

Consider the two-level NML (with B on top) in the upper panel of Figure 1: the parameter ρ_F determines how much "closer" products sharing both B and F are than those sharing only B. In this sense, the NML is parameterizing segmentation along more than one dimension. However, lowering the price of a {B, F} product has the same effect on market shares in the partially matching

{NB, F} category as in the completely unmatching {NB, NF} category.[25] In this sense, the NML permits only one of the two partially matching clusters to be close substitutes. Moreover, reversing the order of nesting just reverses the problem.[26]

These properties can be stated also in terms of cross-elasticities, where $\epsilon_{x,y}$ is the average cross-price elasticity of a product in cluster y with respect to a change in the price of a product in cluster x.[27] According to the two-level nested NML with B/NB on top (as in Figure 1),

$$\epsilon_{bf,bf} \geq \epsilon_{bnf,bf} \geq \epsilon_{nbf,bf} = \epsilon_{nbnf,bf} \tag{8}$$

Reversing the order of nesting renders,

$$\epsilon_{bf,bf} \geq \epsilon_{nbf,bf} \geq \epsilon_{bnf,bf} = \epsilon_{nbnf,bf} \tag{9}$$

Having to choose between (8) and (9) is an uncomfortable specification choice. Neither of the equalities seems likely to hold in the present context, since this case, as many others, is not naturally nested.

The PD GEV overcomes this limitation by permitting both definitions of "local" to work in a parallel fashion (see the second panel in Figure 1), i.e.,

$$\epsilon_{bf,bf} \geq (\epsilon_{nbf,bf}, \epsilon_{bnf,bf}) \geq \epsilon_{nbnf,bf}\,, \quad \text{and} \quad \epsilon_{nbf,bf} \gtrless \epsilon_{bnf,bf} \tag{10}$$

The two principles of differentiation, B and F, are thus treated in a completely symmetric way. Of

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[25] As we have written the model and drawn the picture, it also has the same impact on the outside good. This is not fundamental as it is possible to add a further parameter, say ρ_c, and a third level nest that has all PC's versus the outside good.

[26] As well, a four cluster one-level NML (F/B, F/NB, NF/B, NF/NB) also excludes the possibility of dependence among partially matching products.

[27] For this exercise, assume all products have equal market shares and prices. The elasticities vary with price and market share monotonically. This assumption just simplifies the exposition.

course, this specification is still restrictive, as there are only two parameters permitting more closely related products to be better substitutes. Thus, while the model is no more richly parameterized than the nested logit, it is more appropriate for our specific application which is to identify the impact arising from separate PDs.

V. IMPLEMENTING THE PD GEV MODEL

A. THE ECONOMETRIC PROCEDURE

We outline here the procedure by which the parameters of the PD GEV model can be consistently estimated from a product-level dataset such as the one described in Section III. Essentially, we follow the suggestion of Berry (1994) and construct a GMM estimator from the set of expectations of the level of unobserved product quality, ξ, conditional on the exogenous instruments (discussed below). In order to implement this procedure we need to isolate ξ and express it as a function of data and parameters to be estimated. We are able to do so by "inverting" the demand system. Recall from eq. (7) above that the market share of product j in a market with J products can be written as,

$$s_j = \frac{1}{G(e^{\delta})}\left[a_F \frac{e^{\delta_j/\rho_F}}{\sum_{k\in F(j)} e^{\delta_k/\rho_F}}\left(\sum_{k\in F(j)} e^{\delta_k/\rho_F}\right)^{\rho_F} + a_B \frac{e^{\delta_j/\rho_B}}{\sum_{k\in B(j)} e^{\delta_k/\rho_B}}\left(\sum_{k\in B(j)} e^{\delta_k/\rho_B}\right)^{\rho_B}\right] \qquad \textbf{(11)}$$

Notice that every element of δ, the (J+1) vector of average product quality, enters the market share equation of each product. Thus, with a complete cross-section of products, the market share equations form a system of J equations with (J+1) unknowns (the vector δ). We invert this system for the implicit function $\delta(s, \rho)$. Setting δ_o, the mean value of the outside good, equal to 0, we solve

$$s = s(\delta(s, \rho), \rho) \qquad \textbf{(12)}$$

We use this functional relationship to estimate the parameter vector $\{\hat{\rho}, \hat{\alpha}, \hat{\beta}\}$. We now use our assumption that δ_j is also the average level of utility associated with product j,

$$\delta_j = X_j'\beta + \alpha p_j + \xi_j \tag{13}$$

Rearranging (13) in terms of ξ, and substituting in $\delta(s, \rho)$, we can define the *sample version* of the disturbance for our estimator as,

$$\hat{\xi}_j = \delta_j(s, \hat{\rho}) - (X_j'\hat{\beta} + \hat{\alpha} p_j) \tag{14}$$

Since $E(\xi)=0$, and under the assumption that Z, the matrix of instruments, is exogenous, then the standard GMM estimator is defined as,

$$\underset{\rho,\alpha,\beta}{\text{Min}}\ L = \hat{\xi}'(Z\Omega^{-1}Z')\hat{\xi} \tag{15}$$

where Ω is the standard weighting matrix. Thus, the estimation of the model requires only standard techniques, and is computationally straightforward.[28]

B. INSTRUMENTS

The GMM estimator in (15) requires an instrumental variables (IV) vector, Z, with rank at least as large as the dimensionality of the parameter vector, $\{\beta, \alpha, \rho\}$. Of course, the efficient IV vector is composed of the derivatives of the disturbance (ξ) with respect to the parameters. In the current application it is quite difficult to construct the optimal Z, so we propose a simpler strategy for the construction of Z for PD GEV models.

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[28] As suggested above (and in BLP (1995)), a two-step procedure is appropriate. First, δ is solved for as a function of the observed market shares and a "guess" for ρ (Eq. (12)). This procedure involves a well-behaved numerical nonlinear procedure. With $\delta(s, \rho)$ in hand, the remaining (mean-value) parameters (α,β) can be estimated with a linear instrumental variables estimator. Because the market share function can be expressed in closed form (see (11)), there is no need for integration of the market share function on each iteration of the estimation. This comes at a substantial computation savings relative to the simulated method of moments estimator implemented in BLP (1995). Additional information (including GAUSS estimation programs) are available by public access ftp archive.

Our strategy relies on the econometric exogeneity of the entire matrix of product characteristics, X. In the spirit of the recent literature, we use a model of supply to point out functions of X which make plausible instruments.[29] A row of our proposed Z(X) consists of

- X_j, the observed product characteristics of product j
- counts and means of X for products sharing a cluster with product j
- counts and means of X for products sold by the firm offering product j
- counts and means of X for products sharing both cluster and seller.

This section first visits the general econometrics issues briefly. We then explain how our IV strategy follows from an assumption of equilibrium pricing behavior by sellers in an industry with PD GEV demand.

We face two challenges in constructing Z. With market power on the supply side, it is difficult to justify an assumption that price is independent of ξ; ξ has the interpretation of unobserved product quality, meaning that a higher ξ, should lead suppliers to set a higher p. As a result, $E(P\xi)>0$.[30] Similar arguments mean that the prices and share of other products are correlated with ξ_j, so that the first term as well as the last term in the RHS of (14) calls for IV. To make this more difficult, the econometric framework is inherently nonlinear.[31] In the face of such nonlinearity (and without additional assumptions), the efficient IV vector will contain elements which are themselves functions of the parameters to be estimated, leading to substantial computational difficulties (Chamberlain, 1987).

In response to the difficulties, we propose to utilize our assumption that X, the matrix of observed product characteristics in year t, is exogenous. The immediate implication of this

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[29] Our approach is most like of BLP (1995), who impose some of the economic restrictions of their model on Z(X). Unlike BLP, we offer no proof that our Z is the first under term in a series approximation to the optimal IV.

[30] This problem was emphasized by Trajtenberg (1989, 1990), who found that the demand for CT scanners was estimated to be *positively* sloped in the context of an NML model with exogenous prices. Further analysis revealed that omitted quality, correlated with price, was indeed the culprit for the positive bias. Our solution follows Berry (1994).

[31] $\frac{\partial \xi}{\partial \rho} = \frac{\partial \delta(s,\rho)}{\partial \rho}$ is a highly nonlinear function of ρ.

assumption is that we are able to include x_j directly in Z. This immediately reduces the number of excluded instruments needed to $\dim\{\alpha,\rho\}$. [32]

In general, we are looking for easy-to-calculate variables which are likely to be correlated with price and/or ($\frac{\partial\delta(s,\rho)}{\partial\xi}$) but are independent of ξ. A natural source of instruments for demand coefficients is supply.[33] To highlight this source of instruments, suppose that firms behave according to the solution of a non-cooperative Bertrand-Nash price-setting game. Consider the FOC for product j of a multiproduct firm selling several products, which we represent by the set O(j) (for ownership).

$$P_j = c(q_j,w_j)\ \frac{1}{-\epsilon_{jj}} + \sum_{k\epsilon j}^{m}(p_k - c_k)\ \frac{\epsilon_{kj}}{-\epsilon_{jj}}\frac{q_k}{q_j} \tag{16}$$

Any exogenous variable which shifts the RHS is a candidate instrument.[34] First, we specify PD-specific indices to reflect the number and strength of close substitutes on a group-specific basis. For example, as the number of products in a particular group increases, the demand curve associated with each product in that group will shift in and become flatter in (16). Both effects should impact the observed price and the product's within-group market share. Thus, the number of products in each group will be correlated with the impact of the segmentation parameters, α and ρ, on prices and the implicit function $\delta(s,\rho)$. Essentially, we exploit our assumption that the group-specific entry process is exogenous (in an econometric sense) to create a "local" index of the number of substitutes for each product. As shown in Table 5, we implement this idea by calculating an instrument vector for observation j which includes the number of products in F(j) and B(j), the groups to which product j belongs, as well as sums over the characteristics of other products in F(j) and B(j).

We also calculate "Ownership" instruments (labelled so in Table 5) which exploit the economics of multiproduct pricing as reflected in the RHS of (16). For example, as a particular firm

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[32] In our base model, which has two distributional parameters, each row of Z must have a minimum of (K+3) elements (where K is the number of observed product characteristics).

[33] This approach was critical to the identification of the (simpler) demand models of Bresnahan (1981, 1987), in which model simplicity allowed for the analytical solution of equilibrium prices and market shares.

[34] As in many other industries, it is difficult to obtain observable product-specific cost shifters for PCS; consequently, we do not attempt identification via that route. However, this strategy can sometimes be used appropriately (Bresnahan and Baker, 1986; Hausman, 1994).

sells a larger share of the number of total products available, it will charge a higher price on each product (as compared to the prices which would be observed under a more unconcentrated market structure). Similarly, the sum of the characteristics of the products of the firm (other than j) will be positively correlated with price, since that would mean higher q_k in eq.(16).[35] Finally, we blend these two analytical arguments and use the characteristics and count of products which share both ownership and cluster.

By using PD-specific instruments, we use somewhat different instruments than our immediate predecessors in the literature (BLP (1995)). In particular, we are using our assumption about the group structure of product differentiation to construct the excluded IVS. This strategy is successful because some groups, like Frontier, saw much more entry than others. This entry, which we assume to be exogenous, shifts prices and market shares by changing competition. The different rates of entry across groups means that our proposed instruments vary even in the short panel considered in the present application. It is useful to note that our exogeneity assumption may not be as strong as it seems at first blush. In particular, while we believe that entry into specific clusters is endogenously determined by its economic returns, this does not mean that our instruments are correlated with the error. We include dummies for both B and F in <u>observable</u> product quality; which means that ξ is merely the deviation of the products' quality from the cluster means.

Finally, the discussion so far has been predicated on the assumption that firms engage in Bertrand competition. However, if firms play a different type of non-cooperative game (e.g. Cournot), then the precise form of (16) would change, but our instruments would be unaffected, since the logic of ownership-based and group-based instruments remains the same. Outright collusion though would make a difference, since ownership-based instruments would be longer be relevant. More generally, the point is that the instruments should reflect the underlying supply and demand conditions that prevail in the market, that is, the type of price setting behavior of firms, and the nature of the heterogeneity of consumers as manifested in the groups. For the case at hand, we assume that firms used individualistic pricing strategies; the pace of technical change in PCS and the ensuing intensity of competition seems to have prevented price collusion. However, we will explore the

[35] In this argument we closely follow BLP (1995).

importance of this assumption by removing the ownership-based and PD-based instruments from Z in the course of evaluating the robustness of our results.

VI. RESULTS

We turn now to the presentation and analysis of results from the estimation of the PD GEV for a variety of specifications. We also present estimates of alternative Two-Level NML and VPD models and contrast them with the PD GEV. After exploring the robustness and limitations of the model, we illustrate the meaning of the estimates by drawing hypothetical demand functions for Branded and Frontier PCS and perform a set of counterfactuals involving hypothetical entry to highlight the high degree of market segmentation that these estimates imply.

A. PRINCIPAL FINDINGS

We first preview our main findings (drawn from Model 1 in Table 6) in a concise fashion to help frame the discussion of the results:

(i) $0 < (\rho_F , \rho_B) \ll 1$. Both of the substitution parameters are estimated to be small (significantly smaller than 1), suggesting that there is indeed a high degree of market segmentation along both the B and F dimensions: Non-Branded products are poor substitutes for Branded products and Non-Frontier products are poor substitutes for Frontier products. The parameter ρ_B is estimated quite precisely in most specifications, while the estimate of ρ_F is much less precise. Nevertheless, the estimates for both distributional parameters are quite stable across specifications.

(ii) The product differentiation advantages of B and F are different. The advantage of being at the frontier is limited to the insulation it provides from NF competition ($\rho_F \ll 1$). Perhaps surprisingly, incorporating Frontier technology did not necessarily shift the product demand curve out ($\beta_{FRONTIER}$ is small, usually negative, and always imprecisely estimated). In contrast, having a brand name shifts out the product demand curve ($\beta_{BRAND} > 0$) *and* provides B products with some protection from NB competition ($\rho_B < 1$).

(*iii*) As expected, the price coefficient, α, is sensitive to whether or not the model accounts for price endogeneity, and to the type of instruments used. Models that ignore the correlation of price with unobserved quality result in much smaller (in absolute value) estimates of α; models which do not exploit the full set of proposed instruments severely reduce the precision of this estimate.

(*iv)* The choice of model specification turns out indeed to be important for analyzing the market under study. In fact, the leading alternative to the PD GEV model, the Two-Level NML, yields estimates that are highly sensitive to the order of nesting. In particular, the relative sizes and significance of the substitution parameters are reversed in the Two-Level NML model with the B/NB nest on top, vis a vis the one with the F/NF nest on top. Thus, the PD GEV model offers an attractive methodological alternative, at least in those cases where the nesting order is not well defined a priori.

B. MAIN SPECIFICATION, ROBUSTNESS AND IDENTIFICATION

We present in Table 6 our base specification (Model 1), two alternative specifications in which we vary the elements of X (the set of product characteristics), and a fourth one where we add an additional PD. The parameters estimated are the distributional coefficients ρ_F and ρ_B, a price coefficient, α , various βs (a constant, and coefficients for FRONTIER, BRANDED, IBM, and for a sub-set of DISK, RAM, and MHZ), as well as ρ_{MHZ} in Model 4.

As previewed above, the estimates of ρ_F and ρ_B are quite small in all these specifications. In fact, even though ρ_F is estimated very imprecisely, one can easily reject the hypotheses that ρ_B = 1 and/or ρ_F = 1. The results for the price coefficient, α, are encouraging: it is estimated to be negative and quite stable across specifications; however, its level of significance varies quite a bit (fair in Models 1 and 2, nil in Models 3 and 4). In all four models, the BRANDED coefficient is large, positive, and significant while the FRONTIER coefficient cannot be distinguished from zero (and is in fact negative in three out of four specifications). The IBM coefficient is positive and gives (at the point estimate in the base specification) a 50% incremental boost to IBM products above and beyond other Branded products. Finally, our technological control variables (DISK, RAM, and MHZ) have

the expected sign, though only the DISK coefficient is significant (in Model 1).[36]

It should be noted that the coefficients that determine the level and slope associated with B and F, which are of particular interest here, are relatively stable across the four specifications. Moreover, the point estimates suggest that there was a qualitative difference in the product differentiation advantage afforded along the F versus the B dimension. In fact, we are able to reject the hypothesis:

$$H_0\colon\ \rho_F = \rho_B,\ \beta_F = \beta_B$$

at the 90% level in our main specification (Wald test statistic = 5.22, $\chi^2_{(0.90,\,2)} = 4.61$). While the high standard errors of the F coefficients do not allow us to draw firm conclusions (e.g., we *cannot* reject H_0 at the 95% level), a cautious interpretation of this result is that, relative to the advantages arising from having a brand name, being at the Frontier proved to be beneficial more in the sense of insulating from competition than in pushing out the demand curve. In Model 4 we include a MHZ substitution parameter ($\rho_{MHZ} = .99$).[37] In contrast to the substantial segmentation found along both the B and F dimensions, there seems to be little evidence that there existed segmentation along the MHZ dimension (we cannot reject $H_0\colon\ \rho_{MHZ} = 1$).

In Table 7, we compare the estimates from the PD GEV with those from two alternative specifications of the Two-Level NML model. The most troubling feature of Models 5 and 6 is the high sensitivity of the estimates to the order of nesting. In particular, with B/NB on top, $\rho_B \ll \rho_F$, while the reverse occurs when F/NF is on top. Recall that a small ρ at a given level of the tree signifies poor substitutability of products *across* branches at that level, and hence a high degree of market segmentation according to the PD that governs the split between branches. According to Model 5, the crucial distinction resides in whether a PC is branded or not (ρ_B is both very small and precisely estimated). However, Model 6 implies the opposite, that is, that having Frontier status confers insulation from competition from NF products, whereas Branded status does not provide

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[36] We tried also combinations of these attributes, but the extremely high collinearity between them, as well as between them on the one hand and PRICE and FRONTIER on the other, rendered highly imprecise estimates.

[37] Recall that specifying this model is easy. All that is required is the addition of several terms to (6), each of which is a summation over sets of products which share a similar MHZ rating.

additional protection. Obviously, there is no way of telling within this context which of the two models, contradictory as they are, is the "right" one. In contrast to these awkward modeling choices, the PD GEV confronts the issue of relative importance directly by treating the two principles of differentiation symmetrically.

In Table 8 we vary the instrument set in order to examine the robustness of our findings to alternative identification assumptions. Model 7 treats prices as exogenous, ignoring their presumed dependence on unobserved quality. The result is that the price coefficient shrinks dramatically (in absolute value), providing weak evidence that prices are indeed endogenous (though we cannot reject the overidentifying restrictions). In Model 8, we eliminate the ownership-based instruments, that is, those that stem from the optimizing behavior of multi product firms. Similarly, Model 9 removes PD-based instruments, that is, those associated with the variance in competition across groups. Each of these exercises dramatically reduces the measured precision of the important parameters of the model. The implication is quite clear: to identify our model, we constructed instruments that relied on a behavioral assumption about supply and a structural one about the market. As it turns out, both of these assumptions are necessary in order for us to provide evidence for our main findings.

We ran several other GEV specifications, accounting for serial correlation (across products which appeared in both years), arbitrary heteroskedasticity, and additional potential substitution patterns (e.g., the inclusion of four separate substitution parameters, ρ_B, ρ_{NB}, ρ_F, ρ_{NF}).[38] While there exists no specification in which we can reject the qualitative results described above, the inclusion of additional parameters drastically reduces the precision of most estimates, implying that there is only so much that these data can tell (at least through these models). In other words, the results implied by Model 1 cannot be made more precise by additional modeling. A look at Tables 2 and 4 anew suggests why we cannot hope for finer distinctions: the basic and overwhelming fact that any model would have to accommodate is that IBM accounted for 60% of the market (about 1 million unit sales per year), and the bulk of those sales were in the (B, NF) cluster. By contrast, the average NB/NF (clone) product sold less than 5,000 units/year. Thus, finer distinctions between non-IBM PCS lose out to the stark contrast between IBM and the rest of the pack.

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[38] These sections are not reported in tables but are available from the authors. An ftp archive directory has been set up for public access.

C. A GLIMPSE AT DEMAND CURVES FOR BRANDED AND FRONTIER PRODUCTS

We noted above that the estimates of $\beta_{BRANDED}$ is positive, large, and highly significant, that β_{IBM} is also positive, and that $\beta_{FRONTIER}$ is negative and insignificant. In order to gain further intuition as to the meaning of these results, we take for a moment the point estimates at face value and construct hypothetical demand functions for different types of PCS. Figure 2 displays two hypothetical 1987 demand curves, one associated with a typical IBM, Non-Frontier PC, the other with a typical Non-Branded, Frontier PC. One point on each demand curve is the actual average price and quantities for these two typical products. The other marked point on the demand curve for the IBM/NF PC corresponds to the price at which the mean buyer's valuation of an IBM/NF PC would just equal that of a "clone" product, that is, the price at which $\delta_{IBM,NF} = \delta_{NB,NF}$. Likewise, we calculate the price that renders $\delta_{NB,F} = \delta_{NB,NF}$.

The demand curves thus constructed make it clear that the main advantage of Frontier status, at that very early stage in the diffusion of the 386, seems to have been a steep demand curve rather than a large one (recall the argument in section 2 about the type of users that chose 386-based PCS back then). The converse was true for IBM/Branded status. While we have not estimated equations characterizing sellers' behavior, these demand distinctions would explain why IBM chose to take the bulk of its product differentiation advantage as higher quantities rather than as higher prices (recall the *negative* coefficient on IBM in the hedonic pricing equation (Table 2)), whereas the pioneer manufacturers of Frontier PCS took the reverse course. The two mechanisms of appropriability, the large demand curve and the steep one, were both at work in the industry, but within different PDs.

D. COUNTERFACTUALS

In order to shed further light on the meaning of our findings, we present in Table 9 four counterfactual exercises. In each we introduce a hypothetical new product into a particular cluster and, using the estimates from Model 1, compute the changes in sales of other products that such entry would induce. The main goal is to compare the effects of entry on sales of competing brands within the same cluster, vis a vis the impact on sales in other clusters. We can thus provide a sense of the degree of insulation from competition enjoyed by products in different clusters, as captured by the substitution parameters ρ_F and ρ_B.

In each case, we introduce a hypothetical product with a value of δ (i.e. its expected attractiveness) set equal to the mean value for that cluster.[39] Holding the δs of all other products fixed (which means in particular that we do not allow for any pricing responses to this entry), we recompute the implied market shares for all products, including the outside good. We then calculate the difference in sales for each product before and after the hypothetical introduction. Finally, we sum over all products in each cluster to evaluate the competitive effect of entry across clusters. Consider Table 9 (A), in which an average F/B product is introduced (with $\delta = -5.2$). The model predicts that the sales of this hypothetical PC would total 8511 units, of which 5270 (61%) is "market-stealing" from *within* the F/B cluster. Market-stealing across clusters is significantly smaller, drawing 1700 additional units (20%). The remainder comes from the outside good, that is, from individuals who had not purchased PCS before. In the last part of the table, 9(E), we show a simple market-stealing segmentation statistic and its (linearized) standard error. The numerator is the percentage change in unit sales of existing products within the cluster as a result of the entry experiment. This negative number becomes larger (in absolute value) as the entrant becomes more important and as segmentation becomes more important. The denominator is the percentage change in unit sales of all PC products. This positive number increases with the importance of the product introduced. These statistics confirm the importance of intracluster market stealing implied by the high level of measured segmentation.

While the overwhelming result is that most of the market share of the hypothetical new product comes from *intra*cluster effects, examining the *inter*cluster effects highlights the results of the estimation. The first result is that the effect on the completely non-matching cluster (NF/NB vis a vis F/B) is trivial (16 units). Intercluster market-stealing occurs almost exclusively among the partially matching clusters (NF/B and F/NB). Moreover, while the effect in terms of unit quantities is larger for the cluster which matches along the B dimension (NF/B, which loses 1350 units versus 303 units stolen from the F/NB cluster) the effect in terms of percentages is much larger for the cluster which matches along the F dimension (F/NB, which loses over 1 percent of its unit sales, whereas NF/B's 1350 units represent just *one tenth* of one percent of total units sold).

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[39] For example, in the NB/NF 1988 category, $\delta_{hypo} = -5.44$, the average level of δ in that cluster in 1988.

A similar story (a large *intra*cluster effect, and *inter*cluster effects confined to partially matching clusters) is told in each of the other hypothetical presented in Table 9. For example, a hypothetical low-end clone (NF/NB) sells over 2,500 units, of which only 31 are market-stealing from the Branded group (the B/F and B/NF clusters); an additional 75 are drawn from the F/NB cluster. According to our counterfactuals and contrary to some widely held perceptions of this industry, these clones posed little competitive threat to Branded and Frontier competitors.

VII. CONCLUDING REMARKS

For the last 15 years, the PC industry has been one of the most innovative sectors of the economy; at the same time, it is one of the most competitive. Such conjunction of forces seems to fly in the face of the intuition suggested by Arrow about the necessity of monopoly power in order to induce, and indeed pay for, costly and risky innovation. Where do rents come from in a world where quality-adjusted prices fall at a rate of 25% per year, low-cost imitators keep driving prices ever lower and new distribution channels eradicate the advantages of existing brand capital?

Motivated by a desire to identify the market origins of innovative rents, this paper develops a simple discrete choice model that uses just aggregate data and can easily incorporate prior knowledge of the structure of the industry. We propose the Principles of Differentiation GEV, drawing primarily from McFadden (1978) and Berry (1994). Compared to Multi-Level nested multinomial logit models, ours is not hierarchical; therefore, it does not constrain the cross-elasticities of substitution to conform to a specific order of nesting.

In applying the model to the case of PCS during 1987 and 1988, we begin by noting that the market exhibited two principles of differentiation, according to whether or not the firm could be regarded as having a brand name, and to whether or not the product was at the technological frontier. Much of what follows relies heavily on the above testable hypothesis: the model is structured accordingly (there are two key substitution parameters associated with these PDs); an important subset of the instruments used are predicated on the assumption that these PDs are a good way of slicing the market so as to capture the different degrees of competition faced by products in them; further computations using the estimates are designed so as to compare salient properties of the demand functions facing products in different clusters, and to gauge inter-cluster market-stealing

effects.

The hypothesized PDs also offer a suitable framework to address the puzzles raised above: even if the market as a whole is highly competitive, market segmentation may provide (temporary) insulation from competition in certain clusters. Developing a brand name and/or innovating at the frontier can generate rents by increasing buyers' willingness to pay; depending on the strength and the heterogeneity of this increase, B or F products can have either large demand curves or be poor substitutes for more mundane competitors. Indeed, our findings indicate that competition in the PC market was by no means an all encompassing phenomenon, but that it was largely localized within clusters. Further, having a brand name conferred a large advantage in the sense of shifting out the demand function, whereas being early on at the technological frontier did not.

These results refer just to 1987 and 1988 and, given the rapid pace of change in the industry, one should be wary of using them to interpret the evolution of the PC sector before and after. Yet one inference stands out as eminently plausible: contrary to widely-held perceptions, the demise of IBM as the paramount leader in this industry seems to have been caused not by relentless competitive pressures from clones, but rather by the erosion of IBM's quasi-monopoly stand *within its own cluster*, first by Compaq, then by other entrepreneurial firms that invested heavily on developing a brand name, and in some cases also positioning themselves at the frontier.

The specific, two-way grouping postulated here is just a starting point for what we believe is an appropriate representation of the PC market at the time. Other industries, and perhaps even the PC sector itself at a different time, would require different ways of structuring and grouping the competing products and firms. Indeed, it seems that product differentiated markets very rarely, if at all, consist just of an amorphous collection of n different products produced by m firms. Rather, they appear to be structured according to a few principles of differentiation, which relate in turn to a corresponding menu of strategies opened to firms. A systematic study of those principles, of the way they differ across markets, and of their dynamics seems to be a promising and exciting line of research in empirical Industrial Organization.

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Appendix A
Dataset Methodology and Sources

I. PC DATASET CONSTRUCTION METHODOLOGY

We arrived at the sample of make/models used in the analysis by a process of elimination according to the following criteria. First, we restricted ourselves to products sold by the top 25 vendors of PCs (see Table 1), and eliminated makes for which the number of units sold was less than 300 (approximately equivalent to sales of $1,000,000). This eliminates a substantial number of very small IBM clones, but each of these small vendors accounted for a very small fraction of the business market at the time. In fact, over 90% of the total number of PCs sold in 1987 and 1988 were marketed by the top 25 vendors. Secondly, we constrained the sample to PCs based on Intel microprocessors (the IaPX 80x86 family), including “close” variation from AMD, NEC, etc. The principal alternative microprocessor (Motorola's 68000 family) was incorporated into computers marketed primarily by Apple.[1] These computers were only distant substitutes to Intel-based machines at this time.[2] Finally, we eliminated makes/models for which we could not obtain reliable data on prices and/or characteristics.

II. DATA ON PRICES AND CHARACTERISTICS

Unfortunately there is no single data source which provides consistent and reliable information about the price and characteristics of marketed PCs. Thus, we had to rely on a variety of sources, and invested a great deal of effort in trying to establish consistency and comparability. The primary data source for this purpose was the GML MicroComputer Guide, a quarterly publication which provides list prices and technical characteristics of all PC's marketed. The GML data was complemented and confirmed with an extensive set of additional primary and secondary data sources. These included 1987 and 1988 back issue catalogues and company histories (provided directly by vendors) and a number of contemporary surveys in ComputerWorld, Data Sources, PC World, and PC Technical Journal. Finally, a complementary dataset with prices and characteristics of marketed PCs was graciously provided by Zvi Griliches and Ernie Berndt (see Berndt and Griliches (1993)). In order to be included in the sample, a complete and matched set of prices and characteristics needed to be identified in the GML data or in two or more of the additional sources. For many, if not most, of the observations, we were able to identify at least two mutually consistent sources.[3]

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[1] There were also a small number of PCs (mostly concentrated at the very low or very high end of the quality dimension) which were based on other microprocessors (HP workstations, Commodore PETs, etc.). We excluded them as well from the sample.

[2] Graphics and marketing people tended to purchase Apple technology, whereas accounting, manufacturing, and sales management tended to buy IBM. We experimented with including Apple as an additional Branded firm in the context of nested logit models, but this made little qualitative difference to the estimates. However, we have not conducted such experiments in the context of the PD GEV model.

[3] For a small number of observations, we observed sales in both years but price in only one year. When this occurred, we imposed a price depreciation rate of 10% between the two years.

APPENDIX B

VARIABLE DEFINITIONS

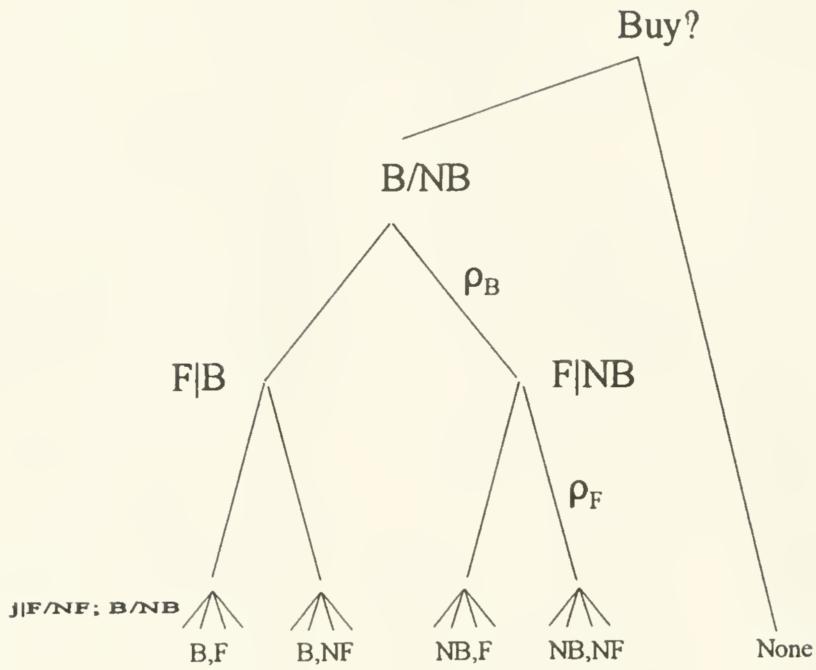
QUANTITY

$QUAN_{j,t}$	Number of PC j Sold in Year t as Estimated by COMTEC Market Analysis Services
$MARKET\ SIZE_{t}$	Total Number of Non-Proprietary Business Office Workers; Includes Workers Who Choose Not to Purchase
$MARKET\ SHARE_{j,t}$	Market Share of Product j in Year t QUAN / 39,000,000

CHARACTERISTICS

$FRONTIER_{j,t}$	Dummy Equal to 1 if Product j Incorporates 80386 Microprocessor
$BRANDED_{j,t}$	Dummy Equal to 1 if Product j is Marketed by IBM, AT&T, HP, or Compaq
$PRICE_{j,t}$	List Price of Product j in Year t as Reported in GML MicroComputer Guide or in Two or More Additional Sources
$RAM_{j,t}$	Standard Random Access Memory (RAM) Provided, in Year t, for Product j; in Kilobytes (KB)
$MHZ_{j,t}$	Standard Microprocessor Speed Provided, in Year t, for Product j; in MHZ
$DISK_{j,t}$	Standard Size of Hard Disk Provided, in Year t, for Product j; in Megabytes (MB)

FIGURE 1
Nested Multinomial Logit and PD GEV



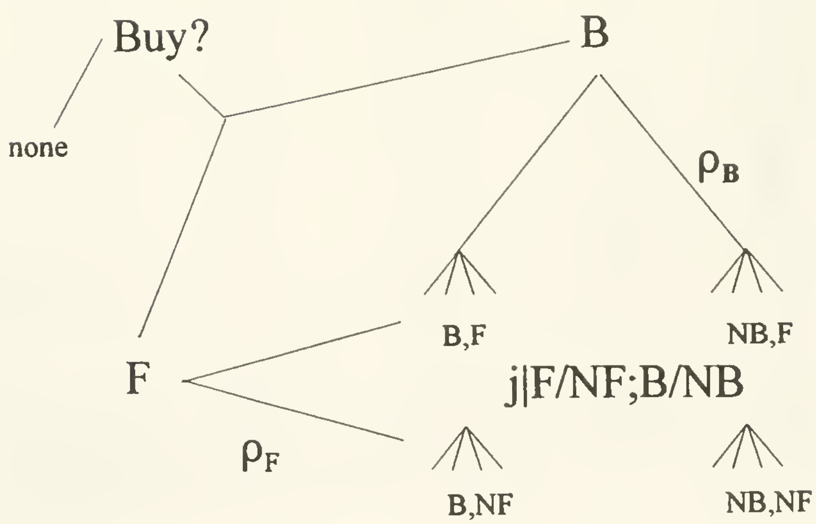


Figure 2
Demand Curves for A Hypothetical IBM/NF Product
and A Hypothetical F, NB Product

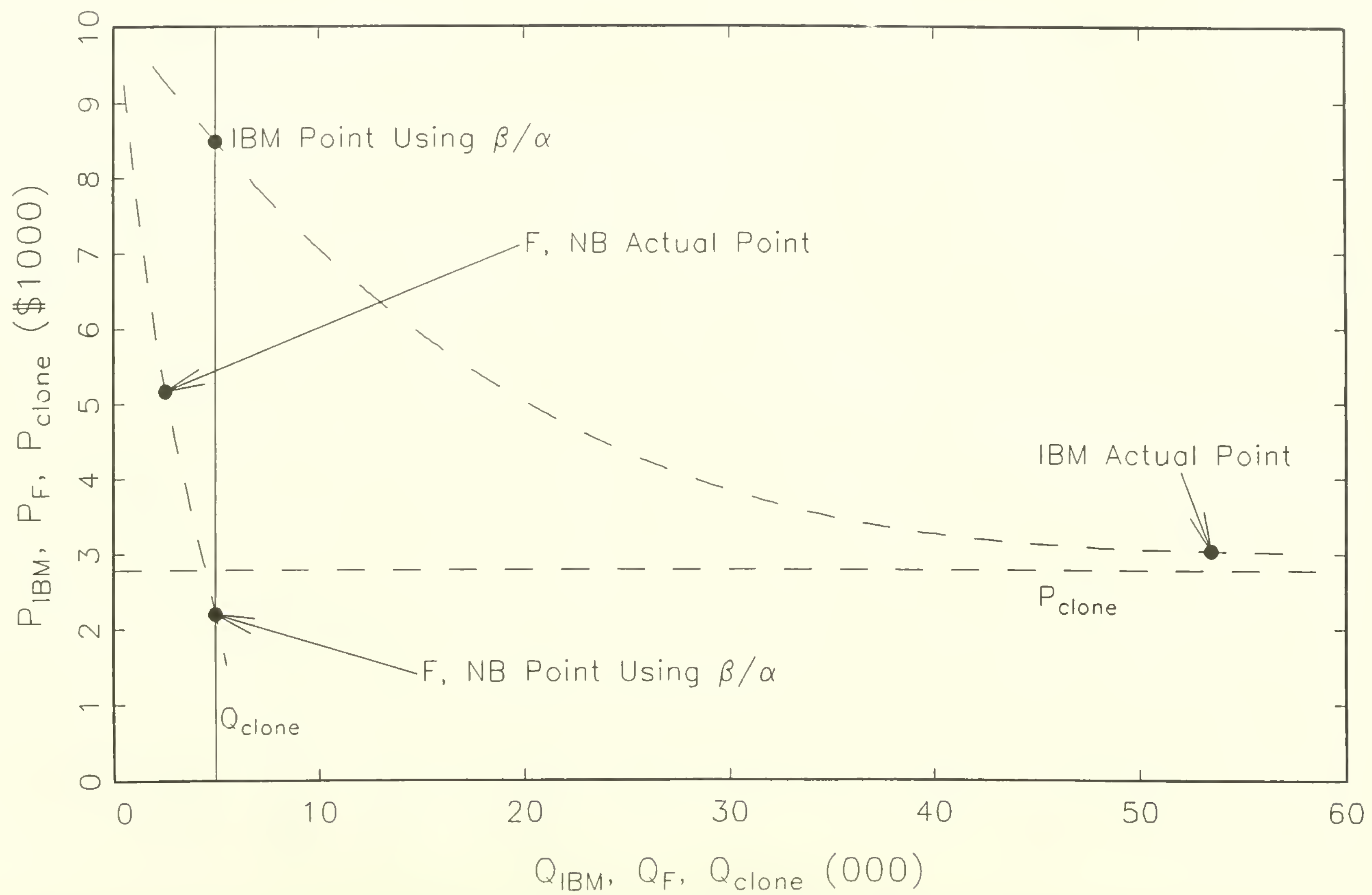


TABLE 1
SUMMARY OF TOP 25 VENDORS

FIRM	PC's SOLD (1987)	PC's SOLD (1988)
Branded		
IBM	943,607	1,025,229
Compaq	128,682	141,621
Hewlett-Packard	58,346	86,904
AT&T	47,168	49,608
Unbranded		
Zenith	79,211	73,100
Radio Shack	75,600	46,030
Epson	37,916	55,015
Leading Edge	35,913	30,042
Sperry	25,773	30,838
Wyse	20,983	19,502
NEC	19,732	28,071
AST	19,722	32,201
Dell	14,836	20,600
Kaypro	13,837	9,393
NCR	12,115	25,713
American Research Corporation	9,108	1,506
Toshiba	8,243	10,823
Memorex	7,080	7,610
Burroughs	6,566	1,134
Wang	4,816	11,337
Datavue	4,594	3,445
DEC	2,609	1,898
Wells-American	2,580	3,492
Xerox	2,270	2,821
Honeywell	1,054	1,239
Total (Branded or Not)	1,582,361	1,719,172

* Firms listed in order of 1987 sales within group.

TABLE 2

SUMMARY STATISTICS BY YEAR

	1987		1988	
	Mean	Standard Deviation	Mean	Standard Deviation
Quantity	13,077	32,856	12,549	28,721
Market Share	.0004	.0008	.0003	.0007
Price	$3,226	$1,692	$3,205	$1,933
Frontier	0.10	0.30	0.15	0.35
Branded	0.30	0.45	0.30	0.45
RAM	611.47	403.73	688.26	504.21
MHZ	8.55	3.75	9.49	4.67
Disk	11.71	17.29	15.43	22.17
# Observations	121		137	

TABLE 3

HEDONIC PRICING EQUATION
1987 & 1988 PC MARKET
(Standard Errors in Parentheses)

DEPENDENT VAR = **PRICE**	**PRODUCT CHARACTERISTICS**
HEDONIC	
1987	1549.69 (1218.95)
1988	1218.95 (232.49)
FRONTIER	1113.16 (314.37)
BRANDED	684.47 (200.90)
IBM	-514.75 (259.30)
MHZ	51.49 (28.89)
RAM	1.08 (0.22)
DISK SIZE	29.20 (4.73)
Adjusted R^2	0.652

TABLE 4

SUMMARY STATISTICS
BY CLUSTER BY YEAR

YEAR = 1987			
		FRONTIER	NON-FRONTIER
BRANDED	# Q P MHZ; RAM; Disk	5 87,058 $7616 17.6; 1424; 59.8	31 1,090,746 $3184 7.6; 506; 11.4
NON-BRANDED	# Q P MHZ; RAM; Disk	7 17,740 $5172 15.4; 1381;14.3	78 386,826 $2786 7.7; 532; 6.5

YEAR = 1988			
		FRONTIER	NON-FRONTIER
BRANDED	# Q P MHZ; RAM; Disk	10 203,466 $7577 19.6; 1531; 62.4	31 1,099,897 $2924 8.0; 493; 13.0
NON-BRANDED	# Q P MHZ; RAM; Disk	10 28,188 $5130 16.4; 1374; 22.0	86 387,631 $2574 8.0; 581; 10.0

Legend	
#	Number of Products
Q	Unit Sales -- Sum of all the products in the cluster
P	Mean Price
MHZ; RAM; Disk	Mean [MHZ, RAM, Disk]

Table 5

Definitions of Instruments
(Used In Model (1))*

Principles of Differentiation

$F(j,t) \equiv$ {other products sold in year t that share F or NF status with product j}

$\sum_{F(j,t)} 1$ $\quad$ $\sum_{F(j,t)} \text{Disk}_k$ $\quad$ $\sum_{F(j,t)} \text{Branded}_k$

$B(j,t) \equiv$ {other products sold in year t that share B or NB status with product j}

$\sum_{B(j,t)} 1$ $\quad$ $\sum_{B(j,t)} \text{Disk}_k$ $\quad$ $\sum_{B(j,t)} \text{Frontier}_k$

Ownership

$O(j,t) \equiv$ {other products sold in year t by seller of product j}

$\sum_{O(j,t)} 1$ $\quad$ $\sum_{O(j,t)} \text{Disk}_k$ $\quad$ $\sum_{O(j,t)} \text{Branded}_k$

Ownership within Principles of Differentiation

$$\sum_{F(j,t)\bigcap O(j,t)} 1$$

$$\sum_{F(j,t)\bigcap O(j,t)} \text{Disk}_k$$

$$\sum_{B(j,t)\bigcap O(j,t)} \text{Disk}_k$$

*Because of multicollinearity among elements of Z, we actually take an orthonormal basis of these instrumental variables in the estimation routine.

TABLE 6

PD GEV MODEL
1987 & 1988 PC MARKET

	BASE (DISK) MODEL (1)	RAM MODEL (2)	MHZ MODEL (3)	VPD (MHZ) MODEL (4)
SUBSTITUTION				
ρ_r	0.1346 (0.1769)	0.1289 (0.1771)	0.1299 (0.1860)	0.1056 (0.1393)
ρ_B	0.3367 (0.0835)	0.3403 (0.0786)	0.3224 (0.0843)	0.2697 (0.1335)
α	-0.00017 (0.00008)	-0.00013 (0.00007)	-0.00014 (0.00010)	-0.00006 (0.00009)
ρ_{MHZ}				0.9998 (0.0112)
β				
CONSTANT	-5.0187 (0.5007)	-5.1773 (0.4477)	-5.1690 (0.5250)	-5.0242 (0.4174)
FRONTIER	-0.0269 (0.3219)	-0.1349 (0.2783)	0.1850 (0.3436)	-0.3513 (0.2620)
BRANDED	0.5674 (0.1030)	0.6181 (0.1326)	0.5664 (0.1217)	0.4872 (0.1141)
IBM	0.2718 (0.1463)	0.2480 (0.1602)	0.3024 (0.1447)	0.2602 (0.1185)
MHZ			0.0248 (0.0255)	0.0091 (0.0205)
RAM		0.0002 (0.0002)		
DISK SIZE	0.0066 (0.0038)			
GMM OBJ (Φ):	2.173	2.356	2.445	3.238

OVERIDENTIFYING RESTRICTIONS TEST:

EQ1 (# OF PARAMS = 8, # of IVs = 13, χ^2 (.95, 5) = 11.07, Φ = 2.173)
EQ2 (# OF PARAMS = 8, # of IVs = 13, χ^2 (.95, 5) = 11.07, Φ = 2.356)
EQ3 (# OF PARAMS = 8, # of IVs = 13, χ^2 (.95, 5) = 11.07, Φ = 2.445)
EQ4 (# OF PARAMS = 9, # of IVs = 13, χ^2 (.95, 9) = 7.82, Φ = 3.238)

TABLE 7

PD GEV VERSUS TWO-LEVEL NML MODELS
1987 & 1988 PC MARKET

	BASE MODEL (1)	TWO-LEVEL NESTED LOGIT (B/NB ON TOP) (5)	TWO-LEVEL NESTED LOGIT (F/NF ON TOP) (6)
SUBSTITUTION			
ρ_F	0.1346 (0.1769)	0.2309 (0.3029)	0.4163 (0.2830)
ρ_B	0.3367 (0.0835)	0.0437 (0.0147)	0.9429 (0.8890)
α	-0.00017 (0.00008)	-0.00004 (0.000007)	-0.00015 (0.00012)
β			
CONSTANT	-5.0187 (0.5007)	-4.4696 (0.0621)	-5.4471 (0.9444)
FRONTIER	-0.0269 (0.3219)	0.0124 (0.0522)	-1.0365 (0.7299)
BRANDED	0.5674 (0.1030)	1.1131 (0.0077)	0.4038 (0.3496)
IBM	0.2718 (0.1463)	-0.0169 (0.0188)	0.4255 (0.2889)
DISK SIZE	0.0066 (0.0038)	0.0021 (0.0003)	0.0076 (0.0055)
GMM OBJ (Φ):	**2.173**	**0.223**	**2.492**

OVERIDENTIFYING RESTRICTIONS TEST:

EQ5 (# OF PARAMS = 8, # of IVs = 13, χ^2 (.95, 5) = 11.07, Φ = 0.223)

EQ6 (# OF PARAMS = 8, # of IVs = 13, χ^2 (.95, 5) = 11.07, Φ=2.492)

TABLE 8

PD GEV MODEL
ALTERNATIVE TREATMENTS OF THE INSTRUMENTS VECTOR
1987 & 1988 PC MARKET

PARAMETERS	PRICE EXOGENOUS (7)	BASE MODEL (1)	NO OWNERSHIP IV (8)	NO PD-SPECIFIC IV (9)
SUBSTITUTION				
ρ_F	0.2782 (0.1441)	0.1346 (0.1769)	0.1232 (2.3257)	0.1324 (0.3195)
ρ_B	0.3285 (0.1242)	0.3367 (0.0835)	0.6734 (4.2001)	0.1886 (0.1461)
α	-0.00007 (0.00003)	-0.00017 (0.00008)	0.00016 (0.00092)	0.00003 (0.00008)
β				
CONSTANT	-5.4692 (0.4061)	-5.0187 (0.5007)	-6.27 (15.99)	-4.7976 (0.4054)
FRONTIER	-0.4067 (0.2582)	-0.0269 (0.3219)	-0.0994 (2.625)	-0.6361 (0.7549)
BRANDED	0.5190 (0.0911)	0.5674 (0.1030)	0.6982 (0.3348)	0.3938 (0.1261)
IBM	0.3627 (0.1296)	0.2718 (0.1463)	0.5884 (4.4384)	0.2046 (0.1135)
DISK SIZE	0.0029 (0.0019)	0.0066 (0.0038)	-0.0069 (0.0308)	-0.0003 (0.0047)
GMM OBJ (Φ):	2.349	2.173	0.526	0.238

OVERIDENTIFYING RESTRICTIONS TEST:

EQ7 (# OF PARAMS = 8, # of IVs = 14, χ^2 (.95, 6) = 12.59, Φ = 2.349)
EQ8 (# OF PARAMS = 8, # of IVs = 8, NO OVERIDENT RESTRICTIONS)
EQ9 (# OF PARAMS = 8, # of IVs = 8, NO OVERIDENT RESTRICTIONS)

Table 9 (A, B)

Demand Impact of Entry of
One Additional F/B Product

Affected Category
Change in Unit Sales
Percent Change

This Product
+8569

Other F/B Products **-5390** *-.0265*	All NF/B Products **-1350** *-.0012*
All F/NB Products **-303** *-.0107*	All NF/NB Products **-16** *-.000041*

Outside Good
-1512
-.000041

One Additional NF/NB Product

Outside good
-806.00
-.0000022

All F/B Products **-5**	All NF/B Products **-26** *-.000024*
All F/NB Products **-75** *-.0027*	Other NF/NB Products **-1590** *-.0000026*

This Product
+2502

Table 9 (C, D)

Demand Impact of Entry of

One Additional F/NB Product

Affected Category

Change in Unit Sales

Percent Change

Outside good
-463
-.0000124

All F/B Products **-196** *-.0010*	All NF/B Products **-14** *-.0000124*
Other F/NB Products **-51** *-.00182*	All NF/NB Products **-854** *-.0022*

This Product
+1578

One Additional NF/B Product

This Product
+7940

All F/B Products **-207** *-.0010*	Other NF/B Products **-5212** *-.0047*
All F/NB Products **-2** *-.000067*	All NF/NB Products **-29** *-.000*

Outside Good
-2490
-.000067

Table 9 (E)

Market-Stealing Segmentation

$$\frac{\Delta Q_{f,b}}{Q_{f,b}} \Big/ \frac{\Delta Q_{PC}}{Q_{PC}}$$

Product Introduced in	1987	1988
F, B	-14.9 (5.4)	-6.5 (4.3)
F, NB	-9.5 (14.9)	-2.8 (1.7)
NF, B	-1.4 (.04)	-1.5 (.03)
NF, NB	-4.0 (.51)	-4.2 (.66)

* Standard errors in parenthesis.